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RESEARCH ARTICLE

Harnessing Data and Technology for Effective Management of Non-Performing Loans: A Systematic Literature Review

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Abstract

This systematic literature review examines the role of emerging technologies, including artificial intelligence, machine learning, blockchain, cloud computing and data analytics, in enhancing the management of non-performing loans. Non-performing loans pose significant risks to financial stability and their effective management is crucial for maintaining the health of financial institutions. This study systematically synthesises existing research to identify how these technologies enhance non-performing loan processes, including identification, monitoring and recovery. The findings reveal that artificial intelligence and machine learning improve non-performing loan detection by analysing borrower behaviour, predicting default risks and enabling proactive risk management. Blockchain ensures secure and transparent loan records, enhancing data integrity and reducing fraud. Cloud computing and data analytics provide scalable solutions for continuous monitoring, while optimisation models and predictive analytics enhance recovery strategies. The review further highlights the influence of macroeconomic factors and bank-specific variables on non-performing loan levels, as well as how technology can mitigate these impacts. This research provides practical insights for financial institutions, regulators and technology providers, offering a roadmap for leveraging advanced technologies to enhance the efficiency of non-performing loan management and mitigate financial risks. Future research should expand its scope by incorporating multiple databases to gain a comprehensive understanding of global trends.

Key Words: *Artificial intelligence; Machine learning; Blockchain; Data analytics; Non-performing loans; Debt recovery; Cloud computing; Systematic literature review*

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1. Introduction

Non-Performing Loans (NPLS) are loans in which borrowers are unable to meet their scheduled payments, typically classified as non-performing when payments are overdue by 90 days or more or if the lender has significant doubts about the borrower's ability to repay in full, regardless of the overdue period [1,2]. In some regions, such as Cyprus, a loan may also be classified as an NPL if it has been restructured or if concessions have been granted to the borrower, even if it is still performing [3]. Additionally, regulatory standards, such as International Financial Reporting Standards (IFRS 9), require banks to classify loans as non-performing if there is a significant increase in credit risk, even without actual default [1]. The acceptable ratio of NPLS can vary by region, banking regulations and economic conditions. In the European Union, the European Banking Authority (EBA) has set a target to reduce NLPs to below 3% of total loans for banks, which has been partially achieved, with the average NPL ratio decreasing from 6% in 2015 to 3% in 2019 [4]. Generally, an NPL ratio below 5% is considered healthy, while a ratio above 10% is often considered a cause for concern, indicating potential instability in the banking sector [2,5]. The importance of managing NPLS cannot be overstated, as they directly impact the stability and profitability of financial institutions and can pose systemic risks to the broader financial system [1,6]. High levels of NPLS can lead to a loss of bank profitability, increase funding costs, restrict credit supply and hinder economic growth, making them a critical area of concern for regulators and policymakers [6,7].

The growth of NPLS is often influenced by a combination of macroeconomic factors, such as economic recessions and bank-specific variables, including poor risk management and governance practices [2,5]. Over the years, the volume of NPLS has increased significantly, particularly during global financial crises. European banks experienced an alarming surge during the 2008 financial crisis and the subsequent sovereign debt crisis [7]. For instance, in the MENA region, NPLS has shown an upward trend, increasing from 6.41% in 2000 to 9.03% in 2019, with Egypt recording the highest NPL ratio among MENA countries, followed by Morocco (11.06%), Jordan (8.52%) and Tunisia (7.12%), while Turkey recorded the lowest at 4.5% due to its stable financial environment [6,8]. These statistics highlight the regional disparity and underscore the urgent need for effective NPL management strategies to maintain financial stability, enhance credit availability and promote sustainable economic development.

Emerging technologies and data analytics have significantly transformed the landscape of NPL management, providing financial institutions with advanced tools for detection, monitoring and mitigation. Financial institutions increasingly adopt Artificial Intelligence (AI), Machine Learning (ML) and big data analytics to enhance their predictive capabilities and risk assessment processes [9]. Specifically, AI-driven models have been employed to identify high-risk loan portfolios, detect fraudulent activities and automate credit scoring, enabling banks to manage NPLS proactively.

Additionally, data analytics help banks optimise their recovery strategies by analysing borrower behaviour, loan performance trends and macroeconomic factors [9]. In the context of NPLS management, these technologies enable banks to transition from reactive to proactive risk management, reducing the volume of NPLS and improving overall financial stability [9]. For instance, cluster detection techniques and optimisation models have been employed to categories NPLS based on their risk profiles, thereby supporting targeted intervention strategies. Moreover, FinTech innovations, including blockchain and cloud-based platforms, have further enhanced data transparency, secure record-keeping and real-time monitoring of loan performance, making NPL management more efficient [9].

These advancements underscore the critical role of emerging technologies in transforming traditional NPL management practices, enabling better decision-making, improved loan recovery and enhanced risk management. Despite significant advancements in emerging technologies such as AI, ML, blockchain, FinTech and cloud computing their adoption of NPLS management remains fragmented. Existing studies primarily focus on the traditional determinants of NPLS, such as macroeconomic factors (e.g., gross domestic product growth, unemployment rate, inflation rate, interest rates, political stability) and bank-specific variables (e.g., credit risk management, loan portfolio composition, profitability, capital adequacy ratio, liquidity ratio, management quality, bank size) but fail to comprehensively explore how these advanced technologies can be systematically integrated to enhance NPL identification, monitoring and recovery [7,10,11].

While AI and ML have shown potential in predictive modelling [12] for credit risk, their application in NPL processes, identification, monitoring and recovery remains underexplored. In addition, blockchain has been highlighted for its ability to provide transparent and secure loan tracking [13], yet its integration with existing NPL processes is still in its infancy, with few studies examining its impact on data integrity and fraud prevention. Similarly, the potential of cloud computing in enabling scalable data analytics for NPL management has not been fully realised, with limited research on how cloud-based platforms can support real-time monitoring and cross-institutional data sharing [14,15].

Conducting a systematic literature review to explore how emerging technologies enhance data analytics and efficiency in NPL management is crucial because it consolidates fragmented knowledge, provides a clear understanding of best practices, highlights existing gaps and guides stakeholders (e.g., financial institutions, regulators and policymakers, technology providers, academic researchers, borrowers and consumers) in leveraging technology to optimise NPL processes. This research gap underscores the need for a systematic literature review to address the following question: How can emerging technologies, such as AI, ML, blockchain, cloud computing and data analytics, enhance the efficiency of NPL management processes and techniques?

This research makes significant practical contributions by providing financial institutions with a comprehensive understanding of how emerging technologies can be integrated and streamlined to manage NPLS. It identifies effective technology-driven strategies for enhancing risk assessment, loan monitoring and recovery processes in banks and lending institutions, ultimately reducing default rates and improving profitability. Regulators and policymakers can leverage the findings to establish best practices and regulatory frameworks that ensure the responsible adoption of these technologies, promoting financial stability and consumer protection.

For FinTech companies and technology providers, the research highlights existing technology gaps and uncovers new opportunities for innovation in NPL management solutions. Moreover, the findings enhance transparency and fairness in lending practices, benefiting borrowers by ensuring NPL management is based on accurate data analytics and equitable decision-making. This research provides a roadmap for integrating emerging technologies into NPL management, enhancing efficiency, compliance and stakeholder confidence in the financial sector.

2. Literature Review

2.1. NPL processes

NPL processing involves three critical stages: identification, monitoring and recovery. Identifying NPLS is the initial step, where banks detect loans at risk of default. They typically use financial metrics such as the NPL ratio, which indicates the percentage of loans that are unlikely to be repaid [16]. Monitoring involves continuous tracking, where banks assess loan performance and identify early warning signs. Financial institutions (e.g. banks) can minimize NPLS by using proactive risk management strategies, such as robust credit assessment [6], enhanced loan monitoring and leveraging data analytics to identify high-risk borrowers early. Recovery focuses on implementing strategies to recover outstanding loan amounts, including restructuring, legal actions or selling non-performing assets [17].

2.2. NPLS and macroeconomic factors

Macroeconomic factors represent external influences and play a critical role in bank profitability and overall performance. These factors significantly impact banks' financial outcomes [18,19] and play a dominant role in enhancing bank performance [14]. Among these factors, inflation has a consistently positive impact on NPLS. Naili, et al. [6] confirmed that rising inflation increases NPLS especially for floating-rate loans, as it erodes purchasing power, making it more difficult for borrowers to meet their obligations. Similarly, Gashi, et al. [20] found a positive and significant relationship between inflation and NPLS reinforcing that inflationary pressures can elevate default risks.

Unemployment is another critical determinant of NPLS. According to Naili, et al. [6], unemployment is a significant factor driving NPLS in emerging economies, where job losses directly impact borrowers' repayment capacity. This finding aligns with Gashi, et al. [20], who also identified a positive relationship between unemployment and NPLS as higher unemployment leads to a loss of income and an increased likelihood of default.

Public debt also exhibits a positive relationship with NPLS, as indicated by Naili, et al. [6], who found that higher levels of public debt correlate with increased NPLS. This suggests that elevated government borrowing can strain the financial system, indirectly affecting borrowers' ability to repay their loans. Interest rates are another significant factor influencing NPLS. Gashi, et al. [20] demonstrated that higher interest rates are associated with increased NPLS, as increased costs place additional financial pressure on borrowers, making them more likely to default.

Gross Domestic Product (GDP), however, presents a contrasting narrative. Gashi, et al. [20] found that GDP has a negative and significant impact on NPLS in the Western Balkans, indicating that economic growth reduces the likelihood of loan defaults as it enhances borrowers' repayment capacity. On the contrary, Naili, et al. [6] reported that GDP growth did not significantly impact NPLS in MENA (Middle East and North Africa) suggesting that economic expansion alone may not effectively reduce default rates.

These findings underscore the pivotal role of macroeconomic stability in reducing non-performing loan (NPL) levels in the financial sector. While some factors, such as inflation, unemployment, public debt and interest rates, directly influence NPLS, the effect of GDP may vary depending on regional economic conditions.

2.3. NPLS and bank-specific variables

Bank-specific variables are critical determinants of NPLS and serve as early warning signals for potential credit risk problems in financial institutions [21]. These variables directly influence credit risk, reflecting a bank's internal management practices, financial health and strategic decisions [21]. According to the research by Naili, et al. [6], several key bank-specific factors significantly impact NPLS, including bank size, capitalisation, performance, loan growth, inefficiency, ownership concentration and diversification. Larger banks, as measured by the natural logarithm of total assets, tend to have lower NPLS due to economies of scale, better risk management and enhanced risk diversification [6]. Similarly, well-capitalised banks (the capital adequacy ratio defines bank capitalisation) experience fewer NPLS because their strong financial buffers absorb potential loan losses. Capital adequacy is a crucial variable, as both studies confirm that higher capitalisation is associated with lower NPLS. A strong capital base enhances depositor confidence and provides a buffer against potential loan losses, minimising credit risk [6,21].

Okoli [21] highlighted that bank profitability/performance, assessed through Return on Equity (ROE), negatively affects credit risk. Profitable banks are less likely to issue risky loans, as strong financial performance reflects high management quality and efficient operations. Loan growth is another significant bank-specific variable that can influence NPLS. In the study by Naili, et al. [6], loan growth, defined as the annual growth rate of gross loans, did not significantly impact NPLS, suggesting that rapid loan expansion does not necessarily lead to higher credit risk. However, Okoli [21] indicated that aggressive loan growth can be a risk factor if not properly managed, as it may increase exposure to borrowers with higher risk profiles. The contrasting findings highlight that the impact of loan growth on NPLS may depend on the quality of credit assessment and risk management practices within the bank.

Furthermore, the research found that bank inefficiency, represented by a higher ratio of operating expenses to operating income, is negatively associated with NPLS, supporting the "skimping hypothesis," which posits that cost-efficient banks maintain healthier loan portfolios [6]. Okoli [21] also emphasised the importance of non-interest income, which allows banks to diversify their earnings rather than relying solely on interest-based income from loans. However, the findings by Naili, et al. [6] show that diversification, measured by the ratio of non-interest income to total income, has an insignificant impact on NPLS, suggesting that non-interest activities may not effectively reduce credit risk in the sampled banks.

The findings also highlight the adverse effect of ownership concentration, represented by the proportion of closely held shares where higher concentrations can increase NPLS due to agency problems and conflicts of interest between majority and minority shareholders [6]. This comprehensive understanding of bank-specific variables underscores their pivotal role in credit risk management. Profitability, capitalisation, loan growth and efficiency emerge as key determinants of NPLS while diversification and ownership concentration present complex and context-dependent effects.

2.4. NPLS techniques

Cluster detection techniques are advanced data analytics methods that group similar data points, particularly in financial data, to enhance understanding of risk patterns and optimise decision-making in NPLS management [22]. These techniques employ adaptive clustering algorithms, such as k-means and Gaussian Mixture Models, which categorise NPLs into distinct risk profiles, allowing for targeted intervention strategies. Furthermore, these

techniques employ algorithms to categorise NPLS into distinct clusters based on their characteristics, such as borrower behaviour, credit history and default risk. In NPLS, cluster detection enables banks to identify high-risk loan portfolios, facilitating more targeted intervention strategies, such as prioritising collections for high-risk groups or exploring restructuring options for moderately risky loans.

Additionally, integrating cluster detection with optimisation models further refines the process by ensuring that each cluster is well-defined and strategically actively managed for better recovery outcomes. This approach enhances the predictive capabilities of financial institutions, enabling them to proactively address NPL risks and improve their overall stability.

Optimisation models leverage a revised Support Vector Data Description (SVDD) model, ensuring compact clusters and effectively managing outliers to enhance NPL management [22]. They are advanced mathematical frameworks used to enhance decision-making in NPLS management by identifying the most efficient strategies for risk mitigation. These models employ various optimisation techniques, including linear programming, mixed-integer programming and multi-objective optimisation to determine the optimal action for minimising NPLS while maximising profitability.

Optimisation models ensure that the clusters remain compact and that data points within a cluster share high similarities. In addition, the optimisation technique is especially effective in reducing the influence of outliers, which are identified and separated, further enhancing the clarity and interpretability of each cluster. For instance, optimisation models can be applied to determine the optimal loan restructuring strategy for distressed borrowers, balancing the trade-off between recovery rates and customer retention. Moreover, in NPL management, banks utilise optimisation models to allocate collection resources effectively, prioritise high-risk accounts and optimise the timing of legal actions or debt restructuring. Such models significantly enhance operational efficiency and financial performance in the banking sector, enabling institutions to proactively manage their NPL portfolios and maintain financial stability.

3. Methodology

Systematic literature reviews advance scholarly understanding by systematically synthesising existing research to provide a comprehensive overview of a given topic. They are instrumental in addressing broad research questions that individual studies may not fully resolve and identifying gaps that present opportunities for future research. This study employs a systematic review methodology to investigate the role of emerging technologies, such as blockchain, AI and ML, in enhancing data analytics techniques and supporting the management of Non-Performing Loans (NPLS). The review adheres to the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, ensuring methodological rigour and transparency. The PRISMA framework provides a structured approach, guiding researchers in clearly defining the review's objectives, procedures and outcomes, thereby enhancing the reliability, validity and reproducibility of the findings [23,24].

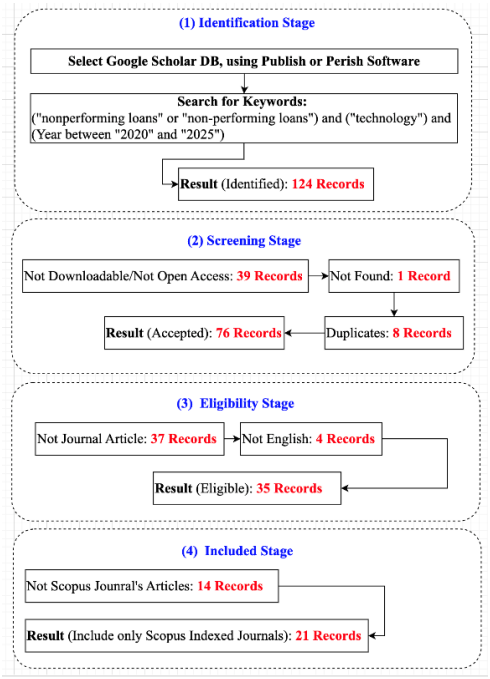
(1) Identification Stage
Select Google Scholar DB, using Publish or Perish Software
Search for Keywords:
("nonperforming loans" or "non-performing loans") and ("technology") and (Year between "2020" and "2025")
Result (Identified): 124 Records
(2) Screening Stage
Not Downloadable/Not Open Access: 39 Records
Not Found: 1 Record
Result (Accepted): 76 Records
Duplicates: 8 Records
(3) Eligibility Stage
Not Journal Article: 37 Records
Not English: 4 Records
Result (Eligible): 35 Records
(4) Included Stage
Not Scopus Jounral's Articles: 14 Records
Result (Include only Scopus Indexed Journals): 21 Records

Figure 1: *PRISMA protocol, a systematic literature review.*

Source: Authors' own creation.

3.1. PRISMA protocol

Following the PRISMA protocol, a systematic literature review is conducted through four key stages: identification, screening, eligibility assessment and inclusion [23]. This study utilizes specialized software tools at each stage to ensure a rigorous and transparent review process. To achieve the study's objectives, articles were retrieved from the Google Scholar database using Publish or Perish software, employing a set of search keywords ("non-performing loans" or "non-performing loans") with a publication range from 2020 to 2025 (Figure 1). Previous studies have demonstrated the validity of conducting systematic literature reviews (SLRs) based on the PRISMA protocol using a single database. For example, Bota-Avram [25] utilised the Web of Science (WOS), Salama, et al. [26] relied on PubMed and Tedja, et al. [27] employed Scopus. Additionally, Aksoy, et al. [28] conducted their SLR using Google Scholar. However, it is generally advised not to rely solely on sources that may include grey literature, such as publications from non-indexed journals. To ensure quality and credibility, it is recommended to complement Google Scholar with other established databases. Accordingly, this study selected only peer-reviewed articles published in Scopus-indexed journals, following the guidance of Haddaway and Yasin [29,30].

The initial search, conducted on May 6, 2025, yielded 124 published records. The review process then adhered to the four PRISMA phases, ensuring a structured approach: (1) Identification, where all potentially relevant articles were collected; (2) Screening, where no open access (not downloadable), not found and duplicate records were removed; (3) Eligibility, where only English journal articles are accepted and (4) Inclusion, where only the Scopus indexed journals of the accepted records are included. Mendeley (version 2.132.1) was used for reference management and organisation to enhance efficiency and transparency, while NVivo (version 15, release 15.1.2) facilitated coding, thematic analysis and descriptive and statistical synthesis. These tools ensured that the review process was systematic, reproducible and fully aligned with PRISMA guidelines.

3.2. PRISMA 4 phases

This study followed the PRISMA 2020 protocol to systematically review the literature, focusing on the technology used to assess NPL processes and techniques. The identification phase began with a comprehensive search in the Google Scholar database, which was specifically chosen due to its broader coverage of published articles on NPLS compared to Scopus. This initial search yielded 124 records. In the screening stage, records were filtered for open-access availability, which is essential for conducting a thorough thematic analysis, ensuring that the full text of each article is accessible for detailed examination. This filtering reduced the selection to 85 articles, with one record not found. Further screening identified eight duplicate records, leaving 76 articles for evaluation. The eligibility phase was refined by focusing exclusively on English-language journal articles. This decision was made to ensure the inclusion of high-quality, peer-reviewed sources while excluding theses, conference papers, working papers and other non-journal publications. This criterion reduced the selection to 35 records. Finally, in the inclusion phase, only those published in journals indexed in Scopus were accepted to guarantee the quality of the journal articles. This quality assurance step resulted in a final selection of 21 accepted articles (Tables 1-3).

4. Thematic Findings

Table 1: *Total publications per journal.*

Journal Name (Scopus Indexed)	Total Publications	Authors
Asian Economic and Financial Review	1	[21]
Baltic Journal of Modern Computing	1	[31]
Cogent Business and Management	4	[32,15,12,33]
Cogent Economics and Finance	1	[34]
FIIB Business Review	1	[19]
Financial Innovation	1	[13]
IEEE Access	1	[35]
International Journal of Professional Business Review	1	[36]
Journal of Ecohumanism	2	[37]
Journal of Economics and Finance	1	[38]
Journal of Financial Regulation	1	[39]
Journal of Modelling in Management	1	[40]
Ikonomicheski Izsledvania	1	[18]
Perspectives on Global Development and Technology	1	[41]
Quantitative Finance	1	[42]
SAGE Open	2	[16,43]
Total	21	

Table 2: *Total publications per year.*

Year	Total Publications	Authors
2020	1	[21]
2021	0	
2022	3	[15,41,44]
2023	7	[13,16,19,31,32,34,38]
2024	5	[33,35,37,40,43]
2025	3	[14,18,42]
Total	21	

Table 3: *The relationship between technology and NPLS management.*

Technology	Relation between Technology and NPLS Management	Authors
FinTech	FinTech enhances consumer well-being by offering innovative and enhanced financial services while minimizing service costs.	[38]
	FinTech represents the integration of technology into financial operations, driving substantial sectoral growth over the past decade.	[38]
	FinTech loan default risk is lower than that of a traditional commercial bank loan.	[13]
	FinTech firms can provide more personalized services based on big data analysis.	[14]
AI	Through the integration of AI, the financial sector is experiencing a digital transformation that is resulting in improved customer experiences, streamlined banking processes and significant changes to industry operations.	[18]
ML	ML techniques can predict non-performing loans using a portfolio dataset.	[35]
	ML's is efficient in integrating corruption indices for better credit risk management.	[12]
	ML models can provide more accurate predictions of non-performing loans.	[12]
Blockchain	Blockchain technology is anticipated to enhance data protection, expedite resolution and automate processes to reduce expenses.	[13]
	Blockchain and other solutions for sharing databases amongst multiple operators and users.	[39]
Big Data, Data Science, Data Analytics	Helps ML techniques to predict the emergence of non-performing loans.	[12]
	Big data helps to tackle information asymmetry.	[15]
	Data science can further explore new dimensions of credit risk and corruption, leading to more comprehensive and effective solutions.	[12]
Cloud-Computing	Support the finance sector and significantly improve production efficiency.	[13]
	Cloud computing in banking operations is cost-effective and flexible for use in consumer payments and customer relationship management.	[14,15]

5. Discussion and Implications

The findings of this study demonstrate how emerging technologies, including FinTech, AI, ML, blockchain, cloud computing and data analytics, significantly enhance the efficiency and effectiveness of NPL management processes and techniques. These technologies enhance the three critical stages of NPL management: identification, monitoring and recovery. In the identification phase, AI and ML algorithms enhance the accuracy of NPL detection by analysing borrower behaviour, credit history and macroeconomic factors, enabling banks to proactively identify high-risk loans [12,35]. For instance, predictive models developed using data analytics can identify patterns associated with default risks, such as declining borrower income, rising interest rates, or adverse economic conditions. Furthermore, blockchain technology offers transparency and security, ensuring that loan records are immutable and tamper-proof, essential for accurate NPL identification [13].

During the monitoring stage, cloud computing and data analytics enhance the continuous tracking of NPLS by providing real-time access to loan performance data and generating automated alerts for early warning signals [12,14,15]. Predictive analytics, powered by ML, can forecast borrower defaults, while cluster detection techniques group loans based on risk profiles, allowing banks to prioritise high-risk accounts for closer monitoring. For example, corruption perception indexes (CPI) and macroeconomic indicators such as GDP, inflation and unemployment can be integrated into predictive models to maintain vigilance over loan portfolios [12]. Additionally, blockchain technology facilitates secure and transparent data sharing between financial institutions, improving coordination in monitoring NPLS [13].

Optimisation models integrated with ML enhance decision-making in the recovery stage by determining the most efficient recovery strategies, such as restructuring, legal action, or debt sales [12,35]. These models allow banks to allocate recovery resources effectively, prioritise high-risk accounts and optimise the timing of legal actions. Blockchain-enabled smart contracts automate payment collections, reducing the administrative burden and ensuring compliance with recovery agreements [13]. Data analytics further support recovery by providing insights into borrower behaviour, enabling banks to customise repayment plans and improve recovery rates [14].

From a broader perspective, these technologies also address macroenvironmental factors that influence NPLS, such as inflation, unemployment, public debt and GDP growth. For example, AI models can forecast the impact of inflation or unemployment on loan defaults, allowing banks to adjust their credit policies proactively [18]. Similarly, blockchain ensures transparency in loan transactions, reducing the risks associated with economic volatility and enhancing borrower trust [39]. Cloud computing facilitates cross-border data sharing, which is crucial for banks operating in multiple regions, thereby ensuring compliance with local macroeconomic conditions. Regarding bank-specific variables, emerging technologies improve credit risk assessment and management practices. For instance, ML models enhance the accuracy of credit scoring, allowing banks to assess borrower creditworthiness more effectively, while blockchain ensures secure record-keeping of borrower histories [12]. Well-capitalised banks can leverage cloud computing for scalable data analytics, improving their ability to monitor loan portfolios and maintain financial stability. Diversified banks can use data analytics to identify profitable non-interest income opportunities, while smaller banks can adopt AI for automated risk assessment, compensating for limited human resources.

6. Conclusion

This study demonstrates that emerging technologies, such as AI, ML, blockchain, cloud computing and data analytics, play a transformative role in enhancing the efficiency of NPL management processes, optimizing NPL techniques and addressing macroenvironmental factors and bank-specific variables. These technologies improve NPL identification through predictive analytics, enhance monitoring with real-time data insights and support recovery with optimisation models. Moreover, they mitigate the impact of macroeconomic fluctuations and enhance the internal risk management practices of financial institutions. Integrating these technologies reduces credit risk and improves banks' financial stability, operational efficiency and profitability. Future research should further explore the integration of these technologies in various financial contexts, with a focus on their long-term impact on NPL management and financial performance.

7. Limitations and Future Research

Although this study offers valuable insights by systematically reviewing literature from the Google Scholar database, its findings are limited by the exclusion of other major academic databases, such as Web of Science (WOS), IEEE Xplore and SpringerLink. Some relevant studies may have been missed, which could limit the scope of the identified relationships between emerging technologies and NPL management processes. To enhance the robustness and comprehensiveness of future research, it is recommended that the dataset be expanded by incorporating multiple databases, thereby providing broader coverage and a more in-depth understanding of global trends. Another limitation of this study is the exclusion of implementation challenges associated with emerging technologies in the context of NPL management.

While the review focuses on the potential benefits of technologies such as blockchain and cloud-based solutions particularly their contributions to data security, operational efficiency and scalability it does not address the practical barriers to their adoption. These may include concerns related to data privacy, regulatory compliance and infrastructural limitations. Although many countries have established robust data protection frameworks and technological infrastructures, this review does not delve into the complexities or readiness levels required for real-world integration. As such, the findings are limited in their ability to address the implementation feasibility of these technologies across diverse contexts.

Furthermore, this study does not provide a comparative evaluation of the relative effectiveness or maturity of the technologies reviewed. The focus of this systematic literature review is to explore how each emerging or advanced technology can contribute positively to the management of NPLs rather than to assess which technology is superior. The technologies discussed, such as AI, blockchain and cloud-based solutions, are often implemented in a complementary manner, with different technologies serving different functional roles within the NPL lifecycle.

As such, this review prioritizes understanding their contributions rather than conducting direct comparisons, which limits the ability to rank or benchmark these technologies against one another. Additionally, this study does not deeply explore the ethical or regional implications of implementing emerging technologies in NPL management. Future research should examine these dimensions more closely, particularly in relation to data privacy, algorithmic fairness and local regulatory frameworks that influence technology adoption across different regions. Finally, one key limitation of this review is the absence of clear

regional or sector-specific delineation. The analysis treats NPL trends and the adoption of emerging technologies as globally uniform without accounting for variations across geographic regions or industry sectors. As a result, the findings may not fully capture the contextual differences in regulatory environments, technological infrastructure and financial system maturity that influence NPL management practices.

8. Declaration and Data availability

8.1. Underlying data

All data underlying the results are available in the article; no additional source data are required. All data have been uploaded (articles) on Dyard (private access).

8.2. Competing interests

No competing interests were disclosed.

8.3. Grant information

The authors declare that no grants were involved in supporting this work.

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